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# Predicting Relations between SOAP Note Sections: The Value of Incorporating a Clinical Information Model

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## Abstract

Physician progress notes are frequently organized into Subjective, Objective, Assessment, and Plan (SOAP) sections. The Assessment section synthesizes information recorded in the Subjective and Objective sections, and the Plan section documents tests and treatments to narrow the differential diagnosis and manage symptoms. Classifying the relationship between the Assessment and Plan sections has been suggested to provide valuable insight into clinical reasoning. In this work, we use a novel human-in-the-loop pipeline to classify the relationships between the Assessment and Plan sections of SOAP notes as a part of the n2c2 2022 Track 3 Challenge. In particular, we use a clinical information model constructed from both the entailment logic expected from the aforementioned Challenge and the problem-oriented medical record. This information model is used to label named entities as primary and secondary problems/symptoms,

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Conflict of Interest Statement

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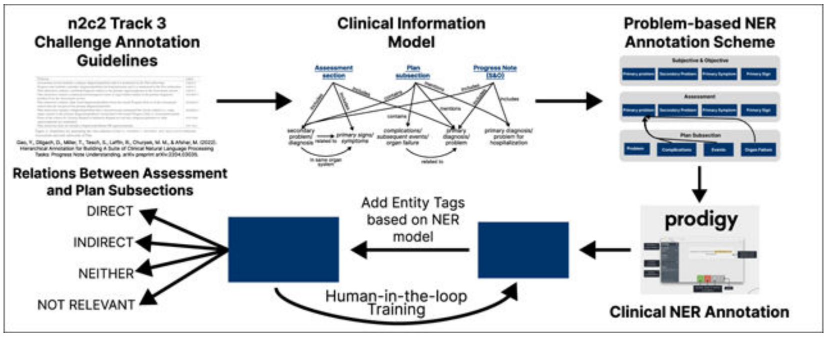
events and complications in all four SOAP sections. We iteratively train separate Named Entity Recognition models and use them to annotate entities in all notes/sections. We fine-tune a downstream RoBERTa-large model to classify the Assessment-Plan relationship. We evaluate multiple language model architectures, preprocessing parameters, and methods of knowledge integration, achieving a maximum macro-F1 score of 82.31%. Our initial model achieves top-2 performance during the challenge (macro-F1: 81.52%, competitors' macro-F1 range: 74.54% −82.12%). We improved our model by incorporating post-challenge annotations (S&O sections), outperforming the top model from the Challenge. We also used Shapley additive explanations to investigate the extent of language model clinical logic, under the lens of our clinical information model. We find that the model often uses shallow heuristics and nonspecific attention when making predictions, suggesting language model knowledge integration requires further research.*

## Graphical Abstract



**Keywords**

natural language processing; language modeling; entailment; SOAP notes; Intensive care unit; electronic health record

## 1. Introduction

### Statement of Significance

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| Problem or Issue | No systems exist that model the relationship between sections of SOAP notes.<br>The extent to which biomedical language models (LMs) perform clinical reasoning with respect to a clinical information model is also poorly understood. |
| What is Already Known | LMs have achieved high performance on sentence-level clinical entailment benchmarks, but SOAP note section-level entailment has not been investigated. |
| What this Paper Adds | This study proposes an information model-based pipeline to model SOAP note section entailment and uses problem-based named entities to investigate LM clinical logic. We also demonstrate the use of an explainable AI method in investigating LM reasoning, identifying key differences between physician and LM decision making. |

A common approach to clinical documentation is the Subjective, Objective, Assessment, and Plan (SOAP) structure, which was first espoused by Weed [35] to aid in clinical reasoning and communication. The SOAP note is oriented around medical problems identified by the physician, qualified by the subjective information gained from the patient and objective information gained from clinical investigations such that they can be assessed and a plan for care put in place. The Assessment section of the note synthesizes and evaluates the information recorded in the Subjective and Objective (S&O) sections to arrive at a differential diagnosis or identify active problems. In the Plan section, tests and treatments needed to narrow the differential diagnosis or provide care are documented. Often, however, there is not an explicit link to Assessment content in the Plan section. Determining the relationship between the Assessment and Plan subsections of the SOAP note would help to model the entanglement of clinical reasoning and documentation, modeling the inferences made following information processing and synthesis necessary to perform the actions of clinical care. Recognizing the significance of these relationships, Track 3 of the 2022 n2c2 Challenge entitled ”Progress Note Understanding: Assessment and Plan Reasoning” tasked participants with developing a model to predict relationships between Assessment and Plan note subsections [8]. The Challenge organizers released a novel set of annotations of SOAP section headings and relations between sections defined by Gao et al. [8] for a patient cohort from MIMIC-III [15]. In this paper we use this newly released corpus and present a top-ranking transformer-based pipeline for the Track 3 Challenge, incorporating a clinical information model into the prediction task.

## 1.1. Related Work

Biomedical relation classification has seen significant progress in recent years, particularly with the advent of transformer-based neural language models (LMs) pretrained on biomedical text such as PubMed Central and MIMIC-III [24]. Most existing tasks focus on relation extraction (RE) using biomedical text, which requires document-level entity recognition prior to relation classification.[17, 4, 12] Few of these methods focus on relation extraction from clinical narratives [10, 34, 28]. In the clinical setting, in addition to classic BERT-based methods, improvements in clinical RE incorporate semantic type information [37] or external knowledge through the use of knowledge graphs [30]. Some methods also leverage LMs such as the Longformer that can incorporate longer-ranged context from clinical notes [19] or utilize multi-task learning paradigms to improve classification [23]. Despite these improvements in relation extraction, Gao et al. [8] present a novel dataset for document-level relation classification over clinical narratives, a setting that hasn’t been previously explored. Moreover, there does not exist a method that incorporates an explicit clinical information model in a neural relation classification system, as we propose in this work.

The theoretical basis for our clinical information model was both the problem-oriented nature of the SOAP note [36] and the classification criteria provided by the n2c2 Challenge [8]. This information model was qualified by the use of entailment graphs to identify the semantic structure of problem-oriented entities (primary and secondary signs, symptoms, complications) relevant to classifying a relationship between the Assessment and Plan subsections.

To distinguish between primary and secondary problems or note complications, events, or organ areas, we label all four note sections using a custom annotation scheme, and train RoBERTa-based Named Entity Recognition (NER) LMs using spacy (details in Section 2.3). Using the trained NER models, we label the text with entity-specific token tags, and further train another biomedical RoBERTa model on the n2c2 Track 3 Challenge data (predicting relationship classes between assessment and plan sections of a SOAP note). We then use an explainable AI method known as SHAP (SHapley Additive exPlanations) to investigate the extent of clinical logic in entailment and classification prediction, analyzing the nature of errors. We find that while primary and secondary problems are accurately recognized and tagged, the entailment LMs often ignores expected clinical logic and entities as described relative to the classification task. Our pipeline without S&O sections achieves top-2 performance (macro-F1: 81.52%), and our final pipeline (macro-F1: 82.31%) outperforms the best model from the Challenge [7] (challenge macro-F1 range: 74.54%−82.12%). We release all code on GitHub[2] and all models on the Hugging Face Model Hub [3] for use by the community.

## 2. Methods

### 2.1. n2c2 Track 3 Challenge Dataset

To address the n2c2 Track 3 Challenge, we develop a novel human-in-the-loop pipeline to classify the relationships between the Assessment and Plan subsections of ICU SOAP notes from the MIMIC-III v1.3 database [15]. The data released as part of the Challenge was drawn from a uniform random sample across 84 different note types, including surgery, medicine, cardiovascular, neurology, and trauma daily progress notes. The Challenge organizers excluded admission notes, discharge summaries, and progress notes written by healthcare providers that do not use the SOAP format (e.g. social work notes). SOAP notes were further filtered to exclude those that only included system-wide assessments as these notes do not follow the problem-oriented format indicative of a SOAP note. The final dataset was annotated using 8 criteria, assigned to 4 different labels: *DIRECT*, *INDIRECT*, *NEITHER*, *NOT RELEVANT*. Relation labels indicate whether a Plan subsection addresses: the primary diagnoses or problems in the Assessment (*DIRECT*), an adverse event or consequence from the primary diagnosis or secondary problem (e.g., comorbidity) in the Assessment (*INDIRECT*), a problem or diagnosis not mentioned in the progress note (*NEITHER*); or does not address a problem or diagnosis listed (*NOT RELEVANT*) (see Gao et al. [8] for additional note filtering details and a full table of criteria and labels for annotation).

The dataset includes a total of 5897 pairs of Assessment and Plan subsections, split into train, development, and test sets (4633 (78.57%), 597 (10.12%), 667 (11.31%) examples, respectively). The demographics of the patient cohort are shown in Table 1, along with its most prevalent diagnoses in Table 2. As mentioned by Gao et al. [8], the cohort includes an oversampling of medical (as opposed to surgical, etc.) notes, as this was the largest service area in the hospital. Following the Challenge, the organizers also released additional annotations which label the SOAP section spans from the entire note (not just assessment/plan sections), under the assumption that including S&O context would improve prediction. We incorporate these additional labels and test this hypothesis.

[2] https://github.com/dchartash/n2c2_2022

[3] https://huggingface.co/vsocrates/n2c2-soap-entailment

## 2.2. Theoretical Model of Clinical Information

With the relationship categories as a target, a pipeline approach was developed building upon a clinical annotation scheme that we believed would improve the LM's clinical entailment by explicitly tagging problem-oriented entities relevant to the patient's admission. This annotation scheme is linked to a theoretical model of problem-oriented medical information which relates to the entailment of clinical problems within the medical record. The entailment of clinical problems can be described by graphs derived from the n2c2 Challenge annotation criteria (examples are shown in Supplemental Figure S1). Consolidating these individual graphs gives rise to a complete model of clinical information, within the context of SOAP note section entailment (Figure 1). The two negative classes, *NEITHER* and *NOT RELEVANT*, are not integrated into the information model for legibility, but it is important to note that all nodes overlap between these subgraphs and the larger information model graph.

In order to define our final annotation scheme, we perform several other preprocessing steps. Certain entailment relations are defined by negative relations within the graph, such as the ones found in the *INDIRECT* relation in Supplemental Figure S1b. We opt to convert these negative relations into positive ones by defining the concept of a secondary diagnosis/problem, which we define as *any diagnosis that is not the predominant reason for the ICU visit*. To capture negative labeling criteria, we add the *secondary problem* label to our clinical information model, as shown. We also separate out the two entities (*complications/subsequent events/organ failure* and *primary signs/symptoms*) such that each of these 5 concepts act as independent entities. These steps lead us to 8 total annotation labels: primary and secondary problems, signs, symptoms, and complications, events, and organ failure, all related to the primary problem. We discuss the specific label sets assigned to each SOAP note section in the following section. The results of the annotation using this information model and subsequent training are shown in Section 3.

## 2.3. NER Annotation and Model Training

Using the clinical information model described in Section 2.2, we identify several common key named entities which revolve around medical problems that we assign as NER labels to each SOAP note section; namely, we annotate the Assessment sections with the primary and secondary problems, as well as signs and symptoms. We annotate the Plan subsections with the primary problem, and the complications, events, and organ failures, each related to the primary problem. We also annotate the Subjective and Objective sections using the Assessment annotation scheme, as these sections capture primary information from the patient within the clinical encounter rather than inferred or evaluated secondary information (as we would expect with complications or events related to a primary problem). That said, progress notes which refer to previous problems replicated in the S&O sections may pose a challenge and this mismatch is described in Section 3 below.

Accurate labeling of relationships therefore depends upon differentiation of primary versus secondary problems and labeling adverse events or consequences of primary problems. Moreover, linking these problems across the Assessment and Plan subsections must account for concept abbreviation (”congestive heart failure” vs. ”CHF”) and semantically similar clinical descriptions (”congestive heart failure” vs ”diastolic failure”). We hypothesize that we can use the aforementioned annotation scheme to annotate a subset of the n2c2 Challenge dataset to improve our downstream Challenge task. The annotation guidelines and rules were initially developed and trialed by a board certified generalist (emergency medicine) physician (RAT). Two medical students (AG, DC) were trained on the annotation scheme. For the annotation task, 240 Assessment and 250 Plan progress notes from the original n2c2 Track 3 Challenge data were randomly selected and uploaded into a Prodigy server environment (see Figure 2). Each medical student annotator labeled all selected notes across the two sections. Discrepancies between the annotators were adjudicated by the board certified physician. To evaluate inter-annotator agreement, we use the F-measure (before adjudication; F=0.6200), as Cohen’s kappa has been shown to be poorly defined for NER tasks [13].

In addition to annotating and developing NER models for the Assessment and Plan subsections, we also annotate 135 Subjective and 135 Objective note sections using the method described above. We hypothesize that including additional context from the SOAP note will improve Challenge task prediction. We also recognize that certain annotation criteria expect information from the entire progress note (see Supplemental Figure S1b).

To support human annotation, we first annotate 100 Assessment and Plan subsections manually using Prodigy, and then use spacy-transformers [4] to fine-tune a general domain RoBERTa-base model [21] pretrained on OntoNotes 5 [26] for both the Assessment and Plan section NER tagging. We employ spacy’s [3] human-in-the-loop training paradigm to perform iterative annotation and model training. The initial model suggests NER labels for annotators to correct. Once the full set of annotations are corrected, we fine-tune a new general domain RoBERTa-base model from scratch using all annotations, split into train and test sets (192 (80%) and 48 (20%)), respectively. For the S&O model, we start with the pretrained Assessment model and further fine-tune it on annotations from concatenated Subjective and Objective note sections using a 90/10 train and test set split (122 (90%), 13 (10%)). The use of an iterative process is intended to reduce annotator cognitive load and speed up the annotation process.

Figure 2 illustrates some of the difficulty in employing our information model in SOAP note annotation. In Figure 2a, we see that the Assessment and Plan subsection have a DIRECT relationship linking the primary problem of *3-vessel disease (3VD)* to the primary symptom of *recurrent chest pain* within the Plan subsection (Figure 2b). However, *3VD* in the Plan subsection could also be considered the problem with *recurrent chest pain* being a symptom, though it was not annotated this way, as shown. The ambiguity associated with selecting a single primary problem among related conditions/symptoms arises due to our Plan subsection annotation scheme, which doesn’t make the distinction between *primary* and *secondary symptoms*, like the Assessment scheme does. We also see that to properly identify this entailment, acronyms such as EF (ejection fraction) and CABG (coronary artery bypass graft) must be disambiguated, necessitating the use of biomedical LMs as shown in Table 4. Finally, in tagging Coronary Artery Bypass Graft Surgery (CABG) as an *Event Related*

[4] https://spacy.io/universe/project/spacy-transformers

*to Primary Problem*, the model fails to perform implicit temporal reasoning, assuming CABG is a physiological consequence following 3VD, instead of a intervention planned for the future. Despite some misalignment between our model of clinical information and the entailment task, we are able to effectively label several named entity types (see Section 3).

## 2.4. Entailment Model Pipeline

Following the annotation of entity spans within the assessment and plan note subsections, we then perform a set of experiments to determine the best downstream model choices for note subsection relation prediction. We first test three different model architectures. As a baseline, we fine-tune the Biomedical RoBERTa-Base model (*Biomed-RoBERTa-Base*) from Lewis et al. [18], pre-trained on PubMed, PMC, and MIMIC-III with a byte-pair encoding (BPE) vocabulary learned from PubMed. We also train the larger, 355M parameter version of this model (*Biomed-RoBERTa-Large*). We only focus on biomedical RoBERTa due to the evidence of significant improvement from in-domain pretraining and vocabulary [33]. Due to the knowledge-intensive nature of this task, we also test SapBERT [20], a PubMedBERT model whose embedding space has been realigned to equate embeddings of UMLS synonyms, encouraging better named entity disambiguation. Finally, we test a generative LM, GPT-NEO 127M [2]. While we were not able to fine-tune this model due to computational constraints, we test its in-context performance against the fine-tuned BERT-based models.

After determining the best model architecture to solve the relation classification task, we also sought to determine the impact of two different knowledge integration methods: either by surrounding text spans with entity tags (as seen in the Assessment section of Figure 5) or by concatenating a list of entities to the end of the raw SOAP note text. Next we perform an ablation study over various text preprocessing steps and training parameters. We tested several approaches such as dictionary-based abbreviation expansion (*Pipeline + Abbreviations*), MIMIC-III de-identification tag replacement (*Pipeline + DeID*), and weighted loss (*Pipeline + Weighted Loss*). For abbreviation disambiguation, we use the Meta-Inventory from Grossman Liu et al. [9], which synthesizes a number of sources including UMLS and Wikipedia. We test de-identification tag replacement as we noticed in preliminary analysis that *Biomed-RoBERTa* poorly tokenizes MIMIC de-ID tags, so we experiment replacing them with placeholders. Following the preprocessing experiments, we investigate the impact of introducing additional context through the integration of the Subjective and Objective sections.

All models were trained with their default parameters from Huggingface transformers v4.25.1 [38], except for Biomed-RoBERTa, which was trained for 15 epochs and a larger learning rate of 1e-5. We train models on the original Challenge dataset, as well as integrate additional S&O context following the Assessment and Plan subsections. To do so, the S&O sections were directly concatenated to the end of the Plan Subsection text. All models used the default maximum sequence length of 512 tokens. For those note pairs that extended beyond this length, the Plan Subsection was truncated. Visual inspection demonstrated less relevant context later in the section than the text that would be truncated in the

Assessment section (e.g. dot phrases, physician signatures). These experiments result in our final pipeline (as shown in Figure 3). We present the results for all experiments in Section 3.

## 3. Results

We report the results of training RoBERTa-base NER models on notes labeled with our information model annotation schemes across all four sections of the SOAP note in Table 3. Using the Assessment annotation scheme, we see that the trained model identified and tagged *primary* and *secondary problems* better than *signs* and *symptoms*. However, this isn't the case when the Assessment scheme is applied to the S&O sections. NER in the S&O sections performed the worst across all entities from any section of the note, though *symptom* recognition was relatively more effective when compared with the Assessment sections. Finally, the model trained using the Plan section annotation scheme performed best in identifying the *primary problem* in that section, but performs significantly worse in identifying inferred or evaluated secondary information (i.e. complications/organ failure).

In Table 4 we show performance metrics for all experiments regarding pipeline choices. All *Pipeline* experiments used *Biomed-RoBERTa* as that performed the best among all model architectures. Similarly, when test- ing S&O integration, we used *Biomed-RoBERTa* with the Assessment and Plan subsections tagged inline, as this performed better than other text preprocessing choices. We find that fine-tuning the Biomed-RoBERTa model on the direct output of the spacy NER models and including the raw S&O section text performs the best, achieving a macro F1 of 82.31% on the validation set and 81.73% on the test set, as shown at the end of Table 4. We also notice that both preprocessing, training choices (weighted loss), and knowledge integration methods have minimal impacts on performance. We only see marginal improvement when the text is tagged with the NER models, yet combined with additional SOAP note context, we outperform the best model of the Challenge [7].

### 3.1. Qualitative Assessment of Annotations

RAT also performed a qualitative assessment of complications during annotation for all four SOAP sections. Annotators found annotating primary and secondary problems in the Assessment section to be straightforward, although in some cases, additional context from the S&O sections was required to distinguish the primary cause for hospitalization. Further, while annotating the S&O sections, annotators identified malformed text, auto-populated templates, and text-based tables which could not classified into an annotation category. Many S&O sections, particularly unconventional ones such as radiology, did not follow the problem-based SOAP note paradigm, making annotation using our primary/secondary problem annotation scheme difficult, as shown in Figure 4.

In this example, the Subjective section (above the dashed line) simply refers to a previous note. Inclusion of a previous review of systems would allow for some annotation using our information model. Similarly, the list of medication, laboratory results, and vitals in the Objective section are difficult to label using the Assessment annotation schema, especially without the full clinical narrative found from other sections of the health record.

## 4. Discussion

In this work, we describe the results of our participation in the n2c2 2022 Track 3 Challenge involving classification of progress note SOAP section relations in the MIMIC-III corpus. The data provided by the Challenge annotators used 8 criteria to classify Assessment and Plan subsections pairs into 4 relations: DIRECT, INDIRECT, NOT RELEVANT, NEITHER. Following the Challenge, organizers also provided span annotations splitting sections into Subjective/Objective/Assessment/Plan subsections. We develop an approach that incorporates a clinical information model into LM-based relation classification by using a custom problem-based NER annotation scheme derived from clinical entailment graphs. We demonstrate that training a Biomedical RoBERTa-large model and including NER annotations of the Assessment and Plan subsections and the raw Subjective & Objective sections performs better than all other pipeline setups. Our results show that this model performs better than the best performing model of the Challenge [7]. As shown in Supplementary Figure S2, AUROC and AUPRC curves demonstrate slight variations in performance between all four classes, though all perform fairly well. Moreover, we develop models that begin to differentiate between primary and secondary problems in clinical notes and explore potential methods of integrating entity-based knowledge into LMs.

Considerable work has been done in designing NLP tasks to integrate aspects of clinical reasoning into LMs [28, 14, 6, 32]. However, despite substantial progress on certain benchmarks [25, 27], LMs have been shown to poorly model clinical reasoning, relying on shallow heuristics and demonstrating an inability to generalize to out-of-sample clinical concepts [11]. Therefore, continued examination of various facets of the problem, including Track 3 of the n2c2 2022 Challenge presented by Gao et al. [8] and discussed in this work, help advance the science. Additionally, a core component of improving LM performance in knowledge-intensive tasks is the integration of external knowledge alongside clinical logic [39, 29, 31]. By using an entailment model which represents clinical information and logic simultaneously, we demonstrate in this work that integrating named-entity based knowledge is non-trivial. We also present a new scheme for annotating clinical problems with respect to SOAP section relationships to facilitate explainable analysis: an information model structured around clinical entailment. Despite our results outperforming the top models on the Challenge task, we identify a number of gaps during error analysis.

### 4.1. Explainability Analysis

While we tried to integrate clinical knowledge into pre-trained biomedical LMs, we notice little improvement when including our entity tagged data. In particular, we used SHAP values [22] to visualize the impact of particular text spans on entailment. Through our error analysis, we identify three limitations in our pipeline: a reliance on shallow relation heuristics, nonspecific attention over S&O sections, and an overall lack of clinical reasoning, all potentially leading to the limited improvements seen in Section 3 from our NER pipeline approach.

As seen from Table 4 and the ROC curves in Supplemental Figure S2, while our model performs well on average, our NER annotation scheme and use of subsequent annotations does not significantly improve results. One reason for this is that often our model relies on syntactic mention-level heuristics for relation prediction. For instance, many DIRECT relations have a *primary problem* surface form in both the Assessment and Plan subsection. The *surface form* of a concept is the form in which the concept appears in the text. Similarly, INDIRECT relations often also feature matching surface forms, but are often preceded by text like *PMH* or *history of*. However, we notice that many incorrect classifications are INDIRECT relations that have no matching surface forms across the two sections, as seen in Figure 6.

While our NER models did not significantly improve prediction, we can still use the annotations to investigate evidence of clinical reasoning performed by the model. For instance, in Figure 5, we see that the model correctly identifies a DIRECT relation which was probably labeled using the criteria, ”Plan subsection contains a problem/diagnosis related to the primary signs/symptoms in the Assessment section.” The model focuses on the occurrence of a matching surface form in both the Assessment and Plan subsection. It further attends to the vitals section of the Objective section, though it doesn’t solely focus on blood pressure (BP), but also includes temperature, heart rate (HR), and respiratory rate (RR), implying that the model’s attention is fairly nonspecific. In Figure 6, we further see evidence of the lack of intrinsic clinical reasoning in entailment prediction. Here we show the same document, with and without the Subjective & Objective sections included. Before the S&O sections are used, the model incorrectly predicts a NEITHER relation, due to the lack of the surface form heuristic. However, once additional context in added, the model adjusts its predict to the correct INDIRECT relation. However, it focuses on general vitals, instead of identifying particular indications of hypothyroidism (such as the Levothyroxine prescription), implying that the model does not employ conventional clinical reasoning to makes its prediction and the inclusion of the S&O components simply provide additional differentiating text to attend over. Reviewing these two examples, we see that our NER models work well for certain concepts (e.g. primary problems, signs, symptoms) and additional context improves prediction. However, our entity tagging did not positively impact entailment due to the model’s seemingly more semantic, rather than clinical, reasoning used in prediction.

A limitation of explainability analysis using this dataset is the lack of the specific annotation criteria used by the Challenge organizers to label note relations. In the example in Figure 6, there is no clear indication in the Assessment section of the nature of the patient’s hypothyroidism. Reviewing the guidelines from Gao et al. [8], we see that an INDIRECT relation can be caused by a Plan subsection containing (1) complications/subsequent events or organ failure related to the primary diagnosis, (2) other listed diagnoses/problems from the overall Progress Note or in the Assessment section that are not part of the primary diagnosis, or (3) a diagnosis/problem that is not previously mentioned but closely related (i.e., same organ system) to the primary diagnosis. Hypothyroidism in a hypotensive patient with a past medical history of cancer presenting with retroperitoneal (RP) bleeding does not seem to fall into either category (1) or (3), as the hypothyroidism is neither a consequence nor in the same organ system as the RP bleed. Hypothyroidism has been shown to be associated with myelodysplastic syndrome (MDS) which could explain an INDIRECT relation [16]. However, this is only true for autoimmune causes of hypothyroidism, such as Hashimoto’s thyroiditis, and the etiology of this patients hypothyroidism is unknown so it is impossible justify the relation with the information given. It is likely the annotators used the mention of Levothyroxine to tag this relation as a category (2) INDIRECT relation, but without these finer grained labels, further interpretation must be speculative.

### 4.2. Implications and Future Work

We design a novel NER annotation scheme that identifies primary and secondary signs and symptoms across SOAP notes from the MIMIC-III corpus, enabling contextual tagging of clinical problems. While our NER models perform adequately, at least with regards to *primary* and *secondary problems* in the Assessment and the *primary problem* in the Plan section, this tagging and subsequent integration into a downstream pipeline does not significantly improve results. Based on our error analysis, we hypothesize that our methods of knowledge integration do not improve token-level embedding representations with respect to clinical reasoning. However, even if our models were able to more effectively integrate knowledge, we see that often SOAP note structures are poorly organized and often do not contain the full information discovered during the clinical encounter in each note, making information extraction (the NER task) and entailment (the relation classification task) difficult. Leveraging additional annotations, particularly from a single institution, to integrate clinical information may also limit generalizability to other institutions. This limitation applies to the Challenge, given that annotations were only provided for critical care notes from a single institution in Boston [15]. Selecting a more nationally representative sample of text for training and testing of both the NER and relation classification models would allow for better generalizability. Additionally, a more robust annotation framework, along with multi-institution annotators, would be necessary to ensure the generalizability of the human-in-the-loop component of the pipeline.

Given the nature of progress notes and evolving care over the course of the encounter, a complete recapitulation of knowledge about the patient in every SOAP progress note seems redundant and a cause of note bloat, a driver of physician burnout [5]. However, interpreting partially reported information from evolving progress notes necessitates better language modeling of the medical record beyond the note, keeping in mind the multi-modal and temporal nature of the documentation of a clinical encounter. Such clinically informed natural language understanding would improve clinical reasoning and entailment problems, such as the one we tackle in this work.

To further refine our pipeline, we plan to continue annotations for our upstream NER models to ensure that we minimize noise and error propagation to downstream steps. This will require upsampling documents that contain less frequent labels (e.g. *Event Related to Problem*). It may also include defining additional entities in our information model, particularly for the S&O sections, that better align with the conventional recording of observations in SOAP notes. We also plan to test other entity-based knowledge integration methods such as TekGen [1], which uses a generative LM to convert KG triples to natural sentences to further fine-tune an LM.

## 5. Conclusion

This work presents a series of experiments addressing the challenge of the classification of relationships between SOAP Assessment and Plan sections. We investigate model architectures, methods of knowledge integration, and text preprocessing choices. We find that an NER pipeline method is the optimal solution for submission to the n2c2 2022 Track 3 Challenge. We further refine this work by integrating the full progress note (S&O sections) upon reflection during the 2022 AMIA Annual Symposium. We demonstrate that a human-in-the-loop approach, combining medical knowledge and diagnostic entity tagging with pre-trained linguistic information contained in LMs, is the most effective method for progress note understanding. We also begin to address the challenge of separating primary and secondary problems, as well as recognizing clinical consequences to these diagnoses in SOAP notes. Finally, we use an explainable AI method to identify and interpret some reasoning gaps by biomedical LMs in note entailment. We release both our entailment model and NER tagging models for future use by the community.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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## Glossary

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| **SOAP** | Subjective, Objective, Assessment, Plan |
| **LM** | Language model |
| **S&O** | Subjective and Objective |
| **NER** | Named Entity Recognition |
| **SHAP** | SHapley Additive exPlanations |

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## Highlights

- The extent to which biomedical language models perform clinical reasoning with respect to a clinical information model is poorly understood.
- Neural language models have achieved high performance on sentence-level clinical entailment benchmarks, but entailment on section-level clinical narratives, such as SOAP notes, has not been investigated.
- This study proposes an information model-based pipeline to model SOAP note section entailment and uses problem-based named entities to investigate LM clinical logic.
- The paper demonstrates the use of an explainable AI method in investigating LM reasoning, identifying key differences between physician and LM decision making.

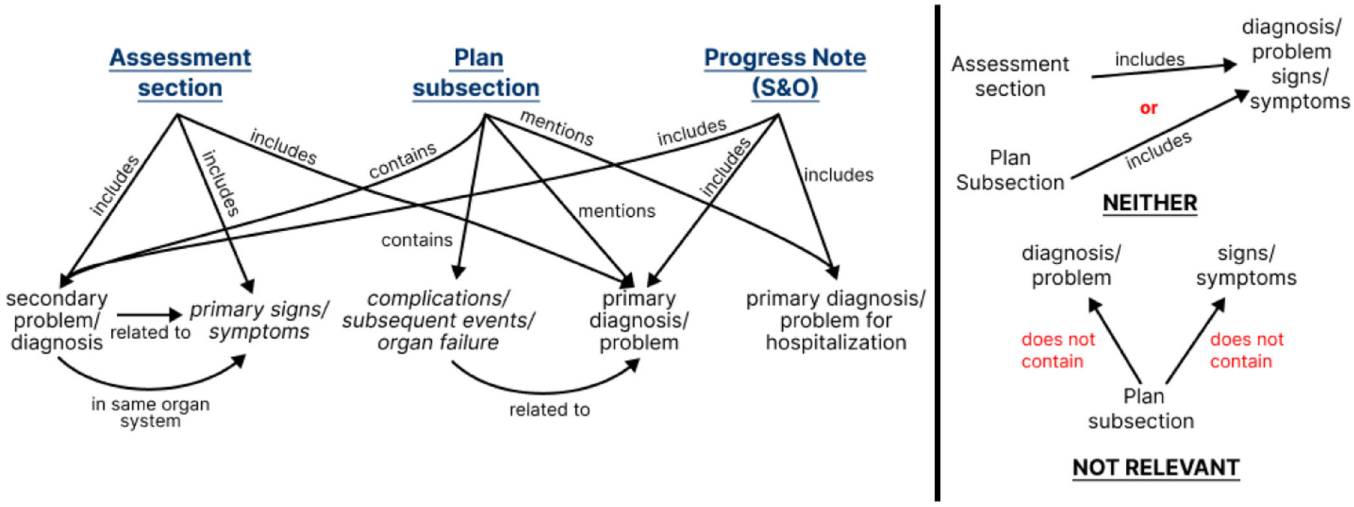
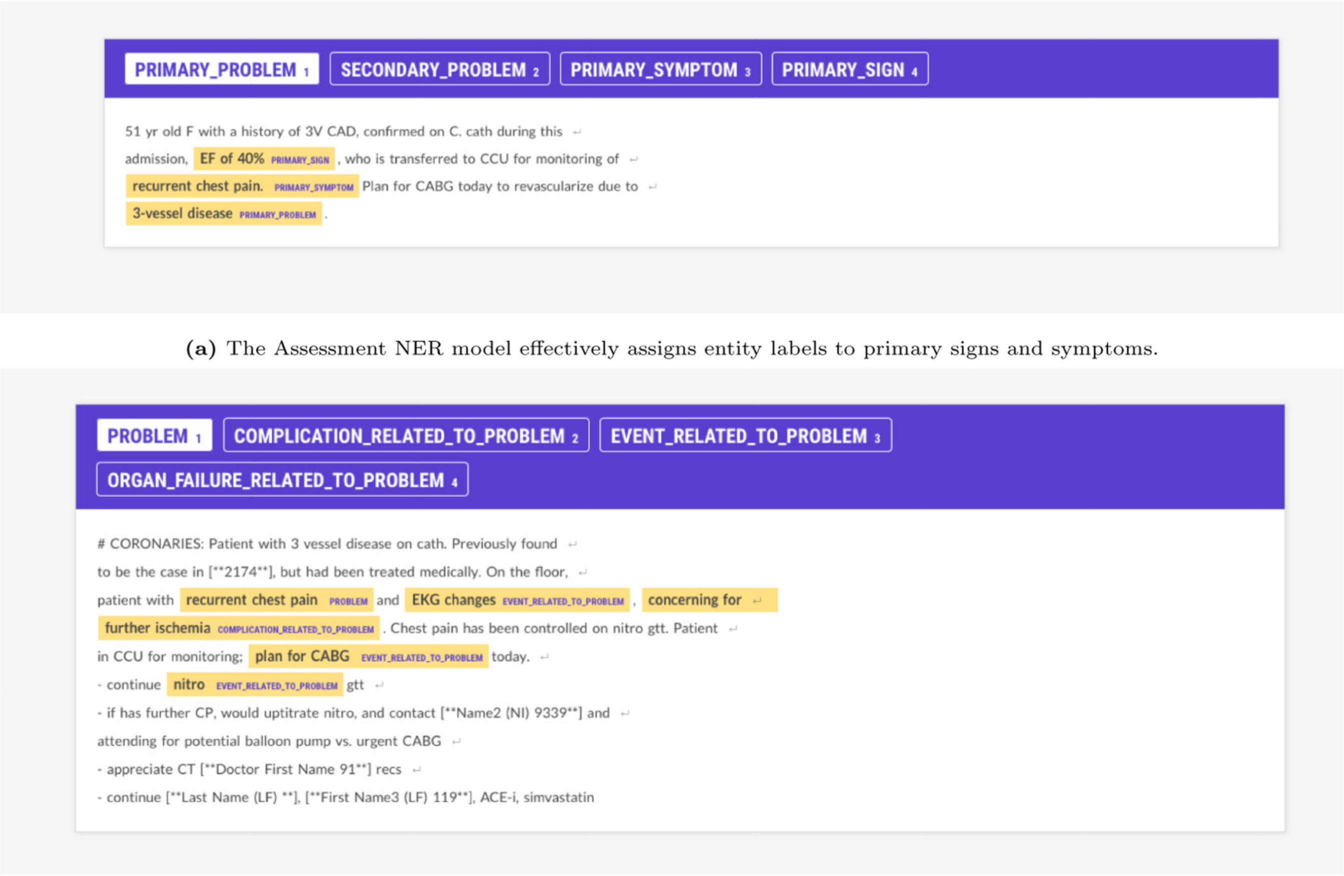


**Figure 1:**

Clinical information model derived from n2c2 annotation guidelines. In blue, we highlight the four sections of the SOAP note. All other nodes in this graph act as named entities to be annotated.


PRIMARY_PROBLEM 1
SECONDARY_PROBLEM 2
PRIMARY_SYMPTOM 3
PRIMARY_SIGN 4

51 yr old F with a history of 3V CAD, confirmed on C. cath during this ↵
admission, EF of 40% PRIMARY_SIGN , who is transferred to CCU for monitoring of ↵
recurrent chest pain. PRIMARY_SYMPTOM Plan for CABG today to revascularize due to ↵
3-vessel disease PRIMARY_PROBLEM .

**(a)** The Assessment NER model effectively assigns entity labels to primary signs and symptoms.

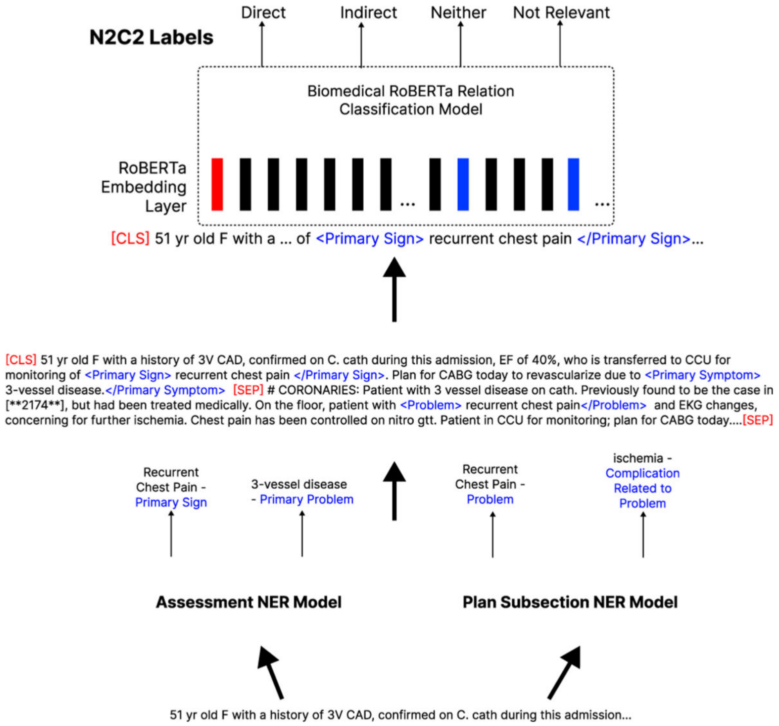
PROBLEM 1
COMPLICATION_RELATED_TO_PROBLEM 2
EVENT_RELATED_TO_PROBLEM 3
ORGAN_FAILURE_RELATED_TO_PROBLEM 4

# CORONARIES: Patient with 3 vessel disease on cath. Previously found ↵
to be the case in [**2174**], but had been treated medically. On the floor, ↵
patient with recurrent chest pain PROBLEM and EKG changes EVENT_RELATED_TO_PROBLEM , concerning for ↵
further ischemia COMPLICATION_RELATED_TO_PROBLEM . Chest pain has been controlled on nitro gtt. Patient ↵
in CCU for monitoring; plan for CABG EVENT_RELATED_TO_PROBLEM today. ↵
- continue nitro EVENT_RELATED_TO_PROBLEM gtt ↵
- if has further CP, would uptitrate nitro, and contact [**Name2 (NI) 9339**] and ↵
attending for potential balloon pump vs. urgent CABG ↵
- appreciate CT [**Doctor First Name 91**] recs ↵
- continue [**Last Name (LF) **], [**First Name3 (LF) 119**], ACE-i, simvastatin

**(b)** The Plan subsection NER model performs well in identifying problems, if they exist.

**Figure 2:**

Screenshots of Prodigy Assessment and Plan subsection annotation interfaces with a *DIRECT* entailment relation

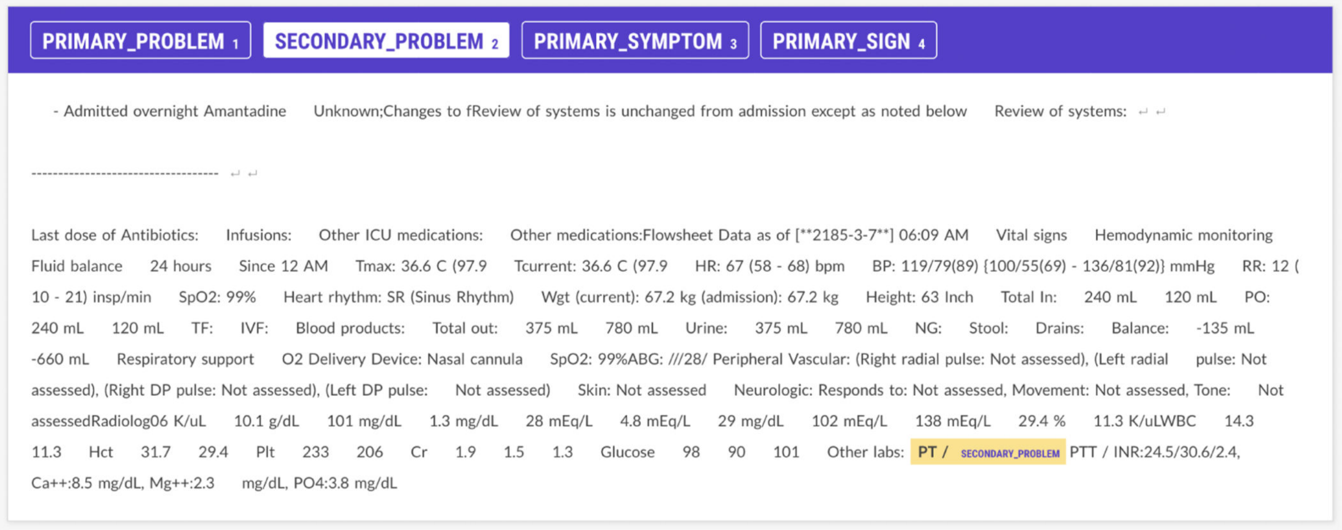


Direct
Indirect
Neither
Not Relevant
N2C2 Labels
Biomedical RoBERTa Relation Classification Model
RoBERTa Embedding Layer
...
...
[CLS] 51 yr old F with a ... of <Primary Sign> recurrent chest pain </Primary Sign>...
Recurrent Chest Pain - Primary Sign
3-vessel disease - Primary Problem
Recurrent Chest Pain - Problem
ischemia - Complication Related to Problem
Assessment NER Model
Plan Subsection NER Model
51 yr old F with a history of 3V CAD, confirmed on C. cath during this admission...

[CLS] 51 yr old F with a history of 3V CAD, confirmed on C. cath during this admission, EF of 40%, who is transferred to CCU for monitoring of <Primary Sign> recurrent chest pain </Primary Sign>. Plan for CABG today to revascularize due to <Primary Symptom> 3-vessel disease.</Primary Symptom> [SEP] # CORONARIES: Patient with 3 vessel disease on cath. Previously found to be the case in [**2174**], but had been treated medically. On the floor, patient with <Problem> recurrent chest pain</Problem> and EKG changes, concerning for further ischemia. Chest pain has been controlled on nitro gtt. Patient in CCU for monitoring; plan for CABG today....[SEP]

**Figure 3:**

Task pipeline including NER pipeline and classification model



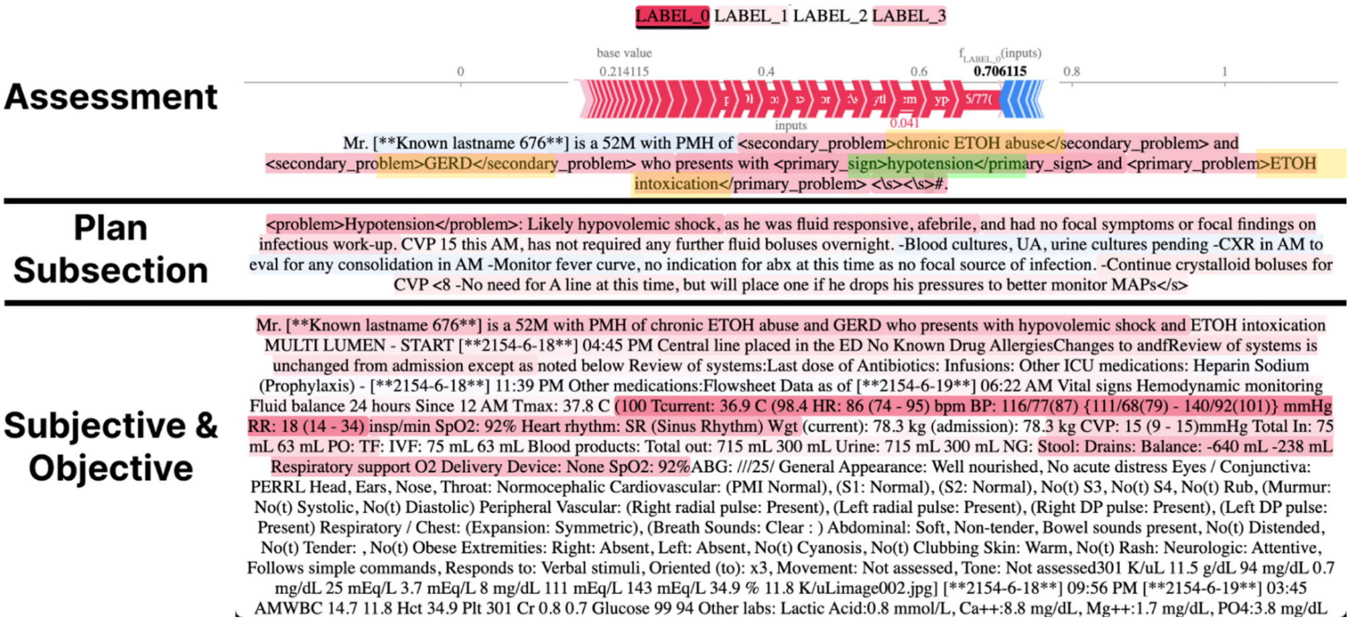
- Admitted overnight Amantadine Unknown;Changes to fReview of systems is unchanged from admission except as noted below Review of systems: ↵ ↵

------------------------------------ ↵ ↵

Last dose of Antibiotics: Infusions: Other ICU medications: Other medications:Flowsheet Data as of [**2185-3-7**] 06:09 AM Vital signs Hemodynamic monitoring Fluid balance 24 hours Since 12 AM Tmax: 36.6 C (97.9 Tcurrent: 36.6 C (97.9 HR: 67 (58 - 68) bpm BP: 119/79(89) {100/55(69) - 136/81(92)} mmHg RR: 12 ( 10 - 21) insp/min SpO2: 99% Heart rhythm: SR (Sinus Rhythm) Wgt (current): 67.2 kg (admission): 67.2 kg Height: 63 Inch Total In: 240 mL 120 mL PO: 240 mL 120 mL TF: IVF: Blood products: Total out: 375 mL 780 mL Urine: 375 mL 780 mL NG: Stool: Drains: Balance: -135 mL -660 mL Respiratory support O2 Delivery Device: Nasal cannula SpO2: 99%ABG: ///28/ Peripheral Vascular: (Right radial pulse: Not assessed), (Left radial pulse: Not assessed), (Right DP pulse: Not assessed), (Left DP pulse: Not assessed) Skin: Not assessed Neurologic: Responds to: Not assessed, Movement: Not assessed, Tone: Not assessedRadiolog06 K/uL 10.1 g/dL 101 mg/dL 1.3 mg/dL 28 mEq/L 4.8 mEq/L 29 mg/dL 102 mEq/L 138 mEq/L 29.4 % 11.3 K/uLWBC 14.3 11.3 Hct 31.7 29.4 Plt 233 206 Cr 1.9 1.5 1.3 Glucose 98 90 101 Other labs: PT / SECONDARY_PROBLEM PTT / INR:24.5/30.6/2.4, Ca++:8.5 mg/dL, Mg++:2.3 mg/dL, PO4:3.8 mg/dL

**Figure 4:**

An image of the Subjective & Objective in Prodigy with limited context that makes problem, sign, and symptom identification difficult.



Assessment

Mr. [**Known lastname 676**] is a 52M with PMH of <secondary_problem>chronic ETOH abuse</secondary_problem> and <secondary_problem>GERD</secondary_problem> who presents with <primary_sign>hypotension</primary_sign> and <primary_problem>ETOH intoxication</primary_problem> <\s><\s>#.

Plan Subsection

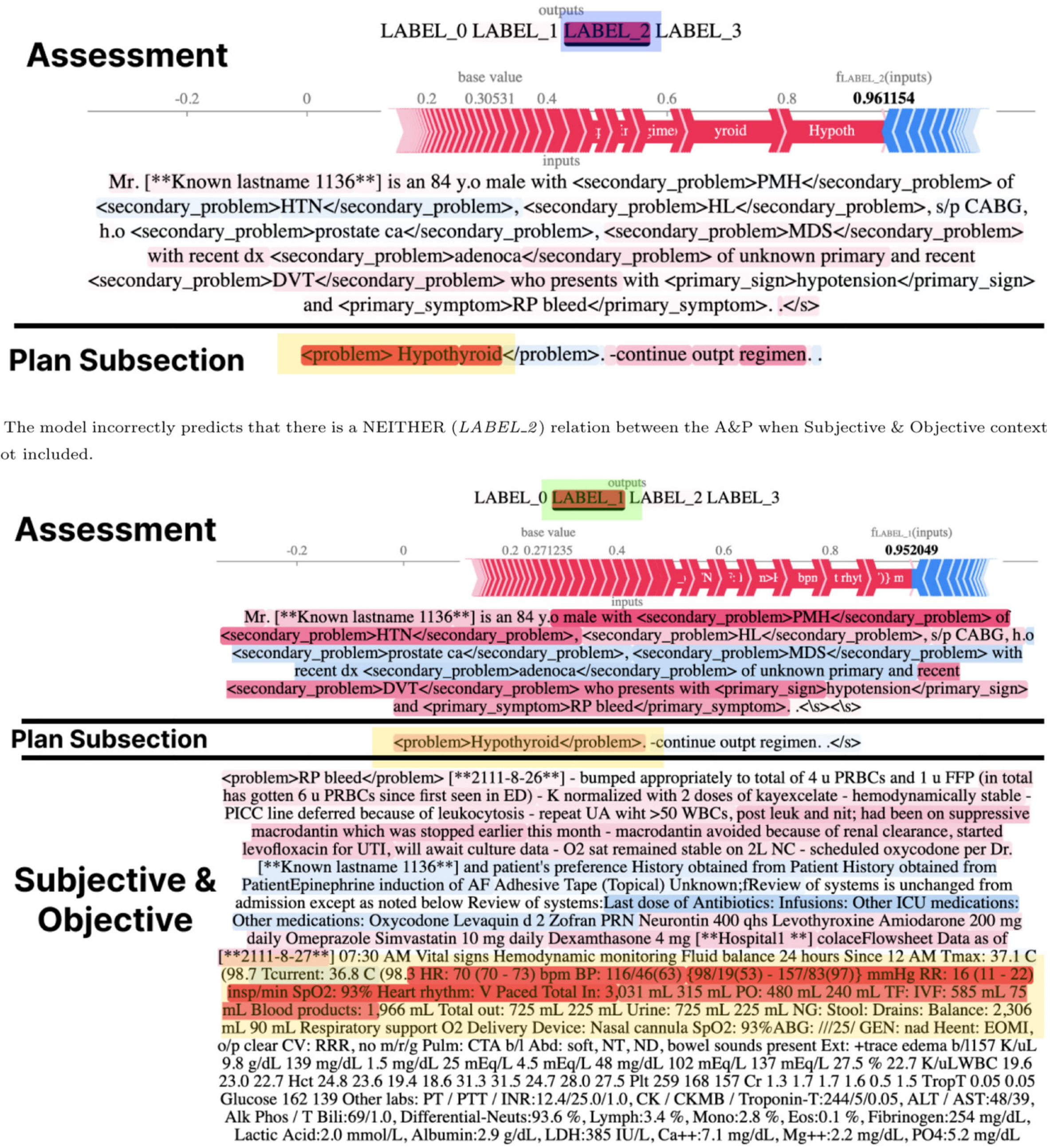
<problem>Hypotension</problem>: Likely hypovolemic shock, as he was fluid responsive, afebrile, and had no focal symptoms or focal findings on infectious work-up. CVP 15 this AM, has not required any further fluid boluses overnight. -Blood cultures, UA, urine cultures pending -CXR in AM to eval for any consolidation in AM -Monitor fever curve, no indication for abx at this time as no focal source of infection. -Continue crystalloid boluses for CVP <8 -No need for A line at this time, but will place one if he drops his pressures to better monitor MAPs</s>

Subjective & Objective

Mr. [**Known lastname 676**] is a 52M with PMH of chronic ETOH abuse and GERD who presents with hypovolemic shock and ETOH intoxication MULTI LUMEN - START [**2154-6-18**] 04:45 PM Central line placed in the ED No Known Drug AllergiesChanges to andfReview of systems is unchanged from admission except as noted below Review of systems:Last dose of Antibiotics: Infusions: Other ICU medications: Heparin Sodium (Prophylaxis) - [**2154-6-18**] 11:39 PM Other medications:Flowsheet Data as of [**2154-6-19**] 06:22 AM Vital signs Hemodynamic monitoring Fluid balance 24 hours Since 12 AM Tmax: 37.8 C (100 Tcurrent: 36.9 C (98.4 HR: 86 (74 - 95) bpm BP: 116/77(87) {111/68(79) - 140/92(101)} mmHg RR: 18 (14 - 34) insp/min SpO2: 92% Heart rhythm: SR (Sinus Rhythm) Wgt (current): 78.3 kg (admission): 78.3 kg CVP: 15 (9 - 15)mmHg Total In: 75 mL 63 mL PO: TF: IVF: 75 mL 63 mL Blood products: Total out: 715 mL 300 mL Urine: 715 mL 300 mL NG: Stool: Drains: Balance: -640 mL -238 mL Respiratory support O2 Delivery Device: None SpO2: 92%ABG: ///25/ General Appearance: Well nourished, No acute distress Eyes / Conjunctiva: PERRL Head, Ears, Nose, Throat: Normocephalic Cardiovascular: (PMI Normal), (S1: Normal), (S2: Normal), No(t) S3, No(t) S4, No(t) Rub, (Murmur: No(t) Systolic, No(t) Diastolic) Peripheral Vascular: (Right radial pulse: Present), (Left radial pulse: Present), (Right DP pulse: Present), (Left DP pulse: Present) Respiratory / Chest: (Expansion: Symmetric), (Breath Sounds: Clear : ) Abdominal: Soft, Non-tender, Bowel sounds present, No(t) Distended, No(t) Tender: , No(t) Obese Extremities: Right: Absent, Left: Absent, No(t) Cyanosis, No(t) Clubbing Skin: Warm, No(t) Rash: Neurologic: Attentive, Follows simple commands, Responds to: Verbal stimuli, Oriented (to): x3, Movement: Not assessed, Tone: Not assessed301 K/uL 11.5 g/dL 94 mg/dL 0.7 mg/dL 25 mEq/L 3.7 mEq/L 8 mg/dL 111 mEq/L 143 mEq/L 34.9 % 11.8 K/uLimage002.jpg] [**2154-6-18**] 09:56 PM [**2154-6-19**] 03:45 AMWBC 14.7 11.8 Hct 34.9 Plt 301 Cr 0.8 0.7 Glucose 99 94 Other labs: Lactic Acid:0.8 mmol/L, Ca++:8.8 mg/dL, Mg++:1.7 mg/dL, PO4:3.8 mg/dL

**Figure 5:**

In this example, the model correct identified a DIRECT relation based on a directly referred sign/symptom. However, when we look at the attention of the tokens over the Assessment text, we see a very nonspecific relationship between all problems, signs, and symptoms mentioned and Hypotension in the Plan subsection. While the model identifies certain relevant clinical features (including low BP in the S&O sections) much of its attention is fairly nonspecific, implying a lack of clinical reasoning in decision making.



Assessment

Mr. [**Known lastname 1136**] is an 84 y.o male with <secondary_problem>PMH</secondary_problem> of <secondary_problem>HTN</secondary_problem>, <secondary_problem>HL</secondary_problem>, s/p CABG, h.o <secondary_problem>prostate ca</secondary_problem>, <secondary_problem>MDS</secondary_problem> with recent dx <secondary_problem>adenoca</secondary_problem> of unknown primary and recent <secondary_problem>DVT</secondary_problem> who presents with <primary_sign>hypotension</primary_sign> and <primary_symptom>RP bleed</primary_symptom>. .</s>

Plan Subsection

<problem> Hypothyroid</problem>. -continue outpt regimen. .

**(a)** The model incorrectly predicts that there is a NEITHER ($LABEL\_2$) relation between the A&P when Subjective & Objective context is not included.

Assessment

Mr. [**Known lastname 1136**] is an 84 y.o male with <secondary_problem>PMH</secondary_problem> of <secondary_problem>HTN</secondary_problem>, <secondary_problem>HL</secondary_problem>, s/p CABG, h.o <secondary_problem>prostate ca</secondary_problem>, <secondary_problem>MDS</secondary_problem> with recent dx <secondary_problem>adenoca</secondary_problem> of unknown primary and recent <secondary_problem>DVT</secondary_problem> who presents with <primary_sign>hypotension</primary_sign> and <primary_symptom>RP bleed</primary_symptom>. .<\s><\s>

Plan Subsection

<problem>Hypothyroid</problem>. -continue outpt regimen. .</s>

Subjective & Objective

<problem>RP bleed</problem> [**2111-8-26**] - bumped appropriately to total of 4 u PRBCs and 1 u FFP (in total has gotten 6 u PRBCs since first seen in ED) - K normalized with 2 doses of kayexcelate - hemodynamically stable - PICC line deferred because of leukocytosis - repeat UA wiht >50 WBCs, post leuk and nit; had been on suppressive macrodantin which was stopped earlier this month - macrodantin avoided because of renal clearance, started levofloxacin for UTI, will await culture data - O2 sat remained stable on 2L NC - scheduled oxycodone per Dr. [**Known lastname 1136**] and patient's preference History obtained from Patient History obtained from PatientEpinephrine induction of AF Adhesive Tape (Topical) Unknown;fReview of systems is unchanged from admission except as noted below Review of systems:Last dose of Antibiotics: Infusions: Other ICU medications: Other medications: Oxycodone Levaquin d 2 Zofran PRN Neurontin 400 qhs Levothyroxine Amiodarone 200 mg daily Omeprazole Simvastatin 10 mg daily Dexamthasone 4 mg [**Hospital1 **] colaceFlowsheet Data as of [**2111-8-27**] 07:30 AM Vital signs Hemodynamic monitoring Fluid balance 24 hours Since 12 AM Tmax: 37.1 C (98.7 Tcurrent: 36.8 C (98.3 HR: 70 (70 - 73) bpm BP: 116/46(63) {98/19(53) - 157/83(97)} mmHg RR: 16 (11 - 22) insp/min SpO2: 93% Heart rhythm: V Paced Total In: 3,031 mL 315 mL PO: 480 mL 240 mL TF: IVF: 585 mL 75 mL Blood products: 1,966 mL Total out: 725 mL 225 mL Urine: 725 mL 225 mL NG: Stool: Drains: Balance: 2,306 mL 90 mL Respiratory support O2 Delivery Device: Nasal cannula SpO2: 93%ABG: ///25/ GEN: nad Heent: EOMI, o/p clear CV: RRR, no m/r/g Pulm: CTA b/l Abd: soft, NT, ND, bowel sounds present Ext: +trace edema b/l157 K/uL 9.8 g/dL 139 mg/dL 1.5 mg/dL 25 mEq/L 4.5 mEq/L 48 mg/dL 102 mEq/L 137 mEq/L 27.5 % 22.7 K/uLWBC 19.6 23.0 22.7 Hct 24.8 23.6 19.4 18.6 31.3 31.5 24.7 28.0 27.5 Plt 259 168 157 Cr 1.3 1.7 1.7 1.6 0.5 1.5 TropT 0.05 0.05 Glucose 162 139 Other labs: PT / PTT / INR:12.4/25.0/1.0, CK / CKMB / Troponin-T:244/5/0.05, ALT / AST:48/39, Alk Phos / T Bili:69/1.0, Differential-Neuts:93.6 %, Lymph:3.4 %, Mono:2.8 %, Eos:0.1 %, Fibrinogen:254 mg/dL, Lactic Acid:2.0 mmol/L, Albumin:2.9 g/dL, LDH:385 IU/L, Ca++:7.1 mg/dL, Mg++:2.2 mg/dL, PO4:5.2 mg/dL

**(b)** The model correctly predicts an INDIRECT relation ($LABEL\_1$) once context has been included.

**Figure 6:**

Model incorrectly labels a note as a NEITHER relation without the Subjective & Objective context, but then adjusts its predict to the correct one with additional context.

## Table 1:

Demographic characteristics of n2c2 MIMIC-III cohort

| n | | Overall 5897 | Direct 1403 | Indirect 1596 | Neither 1882 | Not Relevant 1016 |
|---|---|---|---|---|---|---|
| ADMISSIONTYPE, n (%) | ELECTIVE | 325 (5.5) | 72 (5.1) | 77 (4.8) | 110 (5.8) | 66 (6.5) |
| | EMERGENCY | 5461 (92.6) | 1314 (93.7) | 1491 (93.4) | 1726 (91.7) | 930 (91.5) |
| | URGENT | 111 (1.9) | 17 (1.2) | 28 (1.8) | 46 (2.4) | 20 (2.0) |
| DISCHARGEJLOCATION, n (%) | DEAD/EXPIRED | 696 (11.8) | 165 (11.8) | 195 (12.2) | 231 (12.3) | 105 (10.3) |
| | DISCH-TRAN TO PSYCH HOSP | 70 (1.2) | 17 (1.2) | 20 (1.3) | 18 (1.0) | 15 (1.5) |
| | HOME | 1349 (22.9) | 349 (24.9) | 330 (20.7) | 394 (20.9) | 276 (27.2) |
| | HOME HEALTH CARE | 1397 (23.7) | 310 (22.1) | 397 (24.9) | 448 (23.8) | 242 (23.8) |
| | HOSPICE-HOME | 57 (1.0) | 15 (1.1) | 13 (0.8) | 18 (1.0) | 11 (1.1) |
| | HOSPICE-MEDICAL FACILITY | 19 (0.3) | 5 (0.4) | 2 (0.1) | 8 (0.4) | 4 (0.4) |
| | ICF | 11 (0.2) | 3 (0.2) | 3 (0.2) | 3 (0.2) | 2 (0.2) |
| | LEFT AGAINST MEDICAL ADVI | 103 (1.7) | 18 (1.3) | 24 (1.5) | 43 (2.3) | 18 (1.8) |
| | LONG TERM CARE HOSPITAL | 704 (11.9) | 158 (11.3) | 211 (13.2) | 225 (12.0) | 110 (10.8) |
| | OTHER FACILITY | 23 (0.4) | 5 (0.4) | 8 (0.5) | 7 (0.4) | 3 (0.3) |
| | REHAB/DISTINCT PART HOSP | 325 (5.5) | 83 (5.9) | 85 (5.3) | 97 (5.2) | 60 (5.9) |
| | SHORT TERM HOSPITAL | 63 (1.1) | 13 (0.9) | 23 (1.4) | 19 (1.0) | 8 (0.8) |
| | SNF | 1080 (18.3) | 262 (18.7) | 285 (17.9) | 371 (19.7) | 162 (15.9) |
| INSURANCE, n (%) | Government | 77 (1.3) | 22 (1.6) | 21 (1.3) | 15 (0.8) | 19 (1.9) |
| | Medicaid | 586 (9.9) | 151 (10.8) | 139 (8.7) | 184 (9.8) | 112 (11.0) |
| | Medicare | 3913 (66.4) | 891 (63.5) | 1097 (68.7) | 1304 (69.3) | 621 (61.1) |
| | Private | 1294 (21.9) | 334 (23.8) | 326 (20.4) | 376 (20.0) | 258 (25.4) |
| | Self Pay | 27 (0.5) | 5 (0.4) | 13 (0.8) | 3 (0.2) | 6 (0.6) |
| LANGUAGE, n (%) | **TO | 9 (0.2) | 1 (0.1) | 5 (0.3) | 2 (0.1) | 1 (0.1) |
| | *BUL | 15 (0.3) | 5 (0.4) | 3 (0.2) | 5 (0.3) | 2 (0.2) |
| | AMER | 11 (0.2) | 4 (0.3) | 4 (0.3) | 2 (0.1) | 1 (0.1) |
| | African | 12 (0.2) | 5 (0.4) | 2 (0.1) | 2 (0.1) | 3 (0.3) |
| | CAPE | 45 (0.8) | 9 (0.6) | 17 (1.1) | 12 (0.6) | 7 (0.7) |
| | ENGL | 5220 (88.9) | 1237 (88.5) | 1394 (87.7) | 1686 (90.0) | 903 (89.1) |
| | East Asian | 67 (1.1) | 18 (1.3) | 20 (1.3) | 16 (0.9) | 13 (1.3) |
| | Middle Eastern | 30 (0.5) | 6 (0.4) | 10 (0.6) | 9 (0.5) | 5 (0.5) |
| | PTUN | 134 (2.3) | 29 (2.1) | 42 (2.6) | 37 (2.0) | 26 (2.6) |
| | RUSS | 149 (2.5) | 39 (2.8) | 47 (3.0) | 42 (2.2) | 21 (2.1) |
| | Romance | 183 (3.1) | 45 (3.2) | 46 (2.9) | 61 (3.3) | 31 (3.1) |
| | AMERICAN INDIAN | 24 (0.4) | 5 (0.4) | 3 (0.2) | 13 (0.7) | 3 (0.3) |

| n | | Overall 5897 | Direct 1403 | Indirect 1596 | Neither 1882 | Not Relevant 1016 |
|---|---|---|---|---|---|---|
| ETHNICITY, n (%) | ASIAN | 162 (2.7) | 40 (2.9) | 43 (2.7) | 50 (2.7) | 29 (2.9) |
| | BLACK | 703 (11.9) | 167 (11.9) | 207 (13.0) | 226 (12.0) | 103 (10.1) |
| | HISPANIC/ LATINO | 153 (2.6) | 36 (2.6) | 36 (2.3) | 53 (2.8) | 28 (2.8) |
| | MIDDLE EASTERN | 10 (0.2) | 2 (0.1) | 4 (0.3) | 3 (0.2) | 1 (0.1) |
| | OTHER | 108 (1.8) | 22 (1.6) | 32 (2.0) | 37 (2.0) | 17 (1.7) |
| | PATIENT DECLINED TO ANSWER | 23 (0.4) | 3 (0.2) | 8 (0.5) | 5 (0.3) | 7 (0.7) |
| | UNABLE TO OBTAIN | 68 (1.2) | 15 (1.1) | 22 (1.4) | 21 (1.1) | 10 (1.0) |
| | UNKNOWN/NOT SPECIFIED | 120 (2.0) | 29 (2.1) | 32 (2.0) | 39 (2.1) | 20 (2.0) |
| | WHITE | 4526 (76.8) | 1084 (77.3) | 1209 (75.8) | 1435 (76.2) | 798 (78.5) |
| GENDER, n (%) | F | 2771 (47.0) | 676 (48.2) | 744 (46.6) | 897 (47.7) | 454 (44.7) |
| | M | 3126 (53.0) | 727 (51.8) | 852 (53.4) | 985 (52.3) | 562 (55.3) |

## Table 2:

Top 15 most common diagnoses in n2c2 MIMIC-III cohort

| ICD-9 Prefix | Code Description | Overall | Direct | Indirect | Neither | Not Relevant |
|---|---|---|---|---|---|---|
| 03 | Other Bacterial Diseases | 845 | 196 | 256 | 264 | 129 |
| 42 | Other Forms Of Heart Disease (myocarditis, endocarditis) | 570 | 112 | 152 | 206 | 100 |
| 41 | Ischemic Heart Disease, Diseases Of Pulmonary Circulation | 561 | 131 | 135 | 172 | 123 |
| 57 | Other Diseases Of Digestive System (Chronic liver disease, Cholelithiasis) | 410 | 93 | 111 | 137 | 69 |
| 99 | Other And Unspecified Effects Of External Causes, Complications Of Surgical And Medical Care | 338 | 85 | 96 | 103 | 54 |
| 51 | Other Diseases Of Respiratory System (Pneumothorax, Pleurisy, pulmonary fibrosis) | 331 | 75 | 87 | 120 | 49 |
| 48 | Pneumonia And Influenza | 297 | 73 | 74 | 106 | 44 |
| 56 | Other Diseases Of Intestines And Peritoneum (Intestinal obstruction, diverticula) | 148 | 31 | 51 | 40 | 26 |
| 53 | Diseases Of Esophagus, Stomach, And Duodenum | 145 | 31 | 45 | 38 | 31 |
| 78 | Symptoms | 141 | 35 | 35 | 51 | 20 |
| 25 | Diseases Of Other Endocrine Glands | 122 | 35 | 37 | 34 | 16 |
| 58 | Diseases Of The Genitourinary System | 120 | 25 | 39 | 39 | 17 |
| 27 | Other Metabolic Disorders And Immunity Disorders | 119 | 27 | 24 | 51 | 17 |
| 50 | Pneumoconioses And Other Lung Diseases Due To External Agents | 115 | 29 | 34 | 33 | 19 |
| 59 | Other Diseases Of Urinary System (Calculus, cystitis) | 105 | 29 | 23 | 38 | 15 |

## Table 3:

Assessment, Plan section, and Subjective & Objective NER Model Training Results After Adjudication. We use the same annotation scheme for both the Assessment and the Subjective & Objective (S&O) sections.

| | Entity | Precision | Recall | Macro-Fl |
|---|---|---|---|---|
| Assessment | Primary Problem | 63.83 | 46.88 | 54.05 |
| | Primary Symptom | 48.48 | 66.67 | 56.14 |
| | Primary Sign | 21.74 | 26.32 | 23.81 |
| | Secondary Problem | 78.20 | 75.36 | 76.75 |
| Plan Subsection | Problem | 90.24 | 88.1 | 89.16 |
| | Complication RTP | 40.00 | 10.00 | 16.00 |
| | Event RTP | 25.00 | 12.50 | 16.67 |
| | Organ Failure RTP | 100.00 | 33.33 | 50.00 |
| S&O | Primary Problem | 53.85 | 38.89 | 45.16 |
| | Primary Symptom | 42.86 | 12.50 | 19.35 |
| | Primary Sign | 12.50 | 12.50 | 12.50 |
| | Secondary Problem | 20.00 | 12.50 | 15.38 |

### Table 4:

Macro-F1 scores for all pipeline choices. Underlined values for each subtable indicate the best performing model for a particular set of experiments. The F1 score in bold is the best performing model across all experiments.

| Experiment | Model | Evaluation Set Macro-FI | Test Set Macro-F1 |
|---|---|---|---|
| Model Architecture | GPT Neo-1.7B | 24.70 | 13.11 |
| | SapBERT | 77.46 | 78.4 |
| | Biomed-RoBERTa-Base | 80.34 | 79.36 |
| | Biomed-RoBERTa-Large | 81.71 | 80.77 |
| Knowledge Integration | Pipeline | 81.52 | 81.59 |
| | Pipeline (NER at end) | 81.26 | 82.18 |
| Text Preprocessing | Pipeline + Abbreviations | 80.41 | 80.92 |
| | Pipeline + DelD + Abbvs | 80.30 | 80.68 |
| | Pipeline + Weighted Loss | 81.34 | 81.59 |
| | Pipeline + DelD | 81.17 | 81.55 |
| S&O Integration | Pipeline + S&O | **82.31** | 81.73 |
| | Pipeline + S&O tagged | 79.70 | 84.05 |